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ScienceDirect
Procedia Computer Science 35 (2014) 1436 – 1444
Procedia Computer Science

18th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems - KES2014

Trading agents' negotiation in business management using demand functions: simulation experiments with binomial distribution

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Abstract

The aim of this paper is to propose an experimental business management approach to cover a seller-to-customer price negotiation in an agent-based simulations. The core element in this approach is the price negotiation. We used Marshallian demand function and a Cobb-Douglas utility function in the negotiation process. Moreover, multi-agent model is proposed and implemented in Jade development platform. Its task is to serve as a simulation framework for the trading processes execution. The main background of this framework is to be integrated in management information systems as a decision support module for a prediction of key performance indicators of a virtual company. A binomial distribution was used in presented experiments to simulate the quantity of negotiated commodities. The paper firstly presents some of the existing principles about consumer behavior, agent-based modeling and simulation in the same area and demand function theory. Secondly, presents multi-agent model and demand functions negotiations more formally. Finally, shows some of the simulation results in a trading processes throughout one year of selling commodities to consumers. The results obtained show that the demand functions could be properly used to simulate trading processes.

Peer-review under responsibility of KES International.

Keywords: business; trading; agents; simulation; price negotiation; management; decision support system

1. Introduction

There are many different types of factors in today's global, dynamic and competitive market environment, which the consumers are contemporary dealing with. These factors are difficult to grasp, however, consumers behavior depend on them. The understanding of consumers could overcome some of the problems contemporary businesses

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Peer-review under responsibility of KES International.
doi:10.1016/j.procs.2014.08.202

are dealing with; e.g., Bucki and Suchánek[1]. We concentrate on the use of some economic models and theories in our research to build advanced decision making tools for the business companies. Previously, we presented partial research results using the decision function; e.g., Šperka[2], Šperka et al.[3-4], Šperka and Spišák[5], Šperka and Vymětal[6]; to simulate the trading of a business company, consisting of thousands customers and sellers.

The approach introduced in this paper uses an agent-based model in the form of a multi-agent system to serve as a simulation platform for the seller-to-customer negotiation experiments in a business company. The main idea concentrates around the negotiated price establishment. To cover the price negotiation we used microeconomic demand functions. The overall scenario comes from the research of Barnett[7]. He proposed the integration of the real information system modules with the decision support modules to work together in real-time. The real information system (e.g. ERP – Enterprise Resource Planning system) outputs proceed to the decision support system (in our case the simulation framework) to be used to investigate and to predict important company's metrics (KPIs – Key Performance Indicators). Actual and simulated metrics are compared and evaluated in a management module, which identifies the steps to take to respond in a manner that drives the system metrics towards their desired values. We used a generic control loop model of a business company and implemented multi-agent simulation framework, which represents the decision support system. This task was rather complex, therefore we took only a part of the model – trading processes and the seller-to-customer negotiation concerning the commodities price.

Implemented simulation framework will be a basic part of a future business management system simulating business metrics of a real company's system. The paper is structured as follows. Section 2 represents some of the theoretical incomes. In the section 3 the multi-agent model is described. In the section 4 the seller-to-customer negotiation is introduced. The core of this section are the demand functions definitions. The simulation results are presented in section 5.

2. Related works

With personal and social human factors in consumers behavior deals e.g., Enis[8]. With physical factors deal e.g., McCarthy and Perreault[9]. More complex view on the social, economic, geography and culture factors gave Keegan et al.[10]. Schiffman[11] brought marketing mix and environment into the types of factors mentioned herein above. Previous discussions have so far either relied on an objectivist (complete information of customers, constant decision mechanism, constant consumer preferences) or a constructivist view (consumption discourses, consumption as a crucial aspect in the construction of identity). However, both have failed to integrate the consumers' interactions with their social behavior and physical environment as well as the materiality of consumption; e.g., Gregson et al.[12], and Jackson et al.[13]. The complexity of the factors influencing consumer behavior and their changes in the time shows relations between external stimuli, consumer's features, the course of decision-making process and reaction expressed in his choices. As a result, the investigation of consumer behavior seems to be too complicated for traditional analytical approaches; e.g., Forrester[14], and Challet and Krause[15].

Agent-based modeling and simulation (ABMS) provides some opportunities and benefits resulting from using multi-agent systems as a platform for simulations with the aim to investigate the consumers' behavior. Agent-based models are able to integrate individually differentiated types of consumer behavior. They are characterized by a distributed control and data organization, which enables to represent complex decision processes with only a few specifications. In the recent past there were published many scientific works in this area. They concern in the analysis of companies positioning and the impact on the consumer behavior; e.g., Tay and Lusch[16], Wilkinson and Young[17], and Casti[18]. Often discussed is the reception of the product by the market; e.g., Goldenberg et al.[19], and Heath et al.[20]; and innovation diffusion; e.g., Rahmandad and Sterman[21], Shaikh et al.[22], Toubia et al.[23], and Laco[24]. More general deliberations on the ABMS in the investigating of consumer behavior show e.g., Adjali et al.[25], Ben et al.[26], and Collings et al.[27].

The core problem to be solved in the business process of selling the commodities to consumers while using the simulation is the price negotiation. We used some predefined functions from economic theory in this partial research. We built our experimental research on a demand functions. In microeconomics, a consumer's Marshallian demand function (named after Alfred Marshall) specifies what the consumer would buy in each price and wealth situation according to Marshall[28], assuming it perfectly solves the utility maximization problem. Marshallian demand is sometimes called Walrasian demand (named after Léon Walras) or uncompensated demand function instead, because the original Marshallian analysis ignored wealth effects; e.g., Mas-Colell et al.[29], and Pollak[30]. We also used a Cobb-Douglas utility function and preferences saying that the quantity demanded for each commodity does not depend on income, in fact quantity demanded for each commodity is proportional to the income according to Varian[31]. We based the seller-to-customer negotiation in our virtual company simulations on these two approaches. In the next section the business model is introduced.

3. Business model

Business model consists of the following types of agents: sales representative agents (representing sellers, seller agents), customer agents, informative agent (measures time, informs agents about period passing), and manager agent (manages the seller agents, calculates KPI). After a design phase a simulation framework, based on the business model was implemented and used to trigger the simulation experiments to ensure the outputs of trading processes simulations. The framework covers processes supporting the selling of commodities by company sales representatives to the customers – seller-to-customer negotiation (Fig. 1). All the agent types were developed according to the multi-agent approach. The interaction between agents is based on the FIPA[32] contract-net protocol.

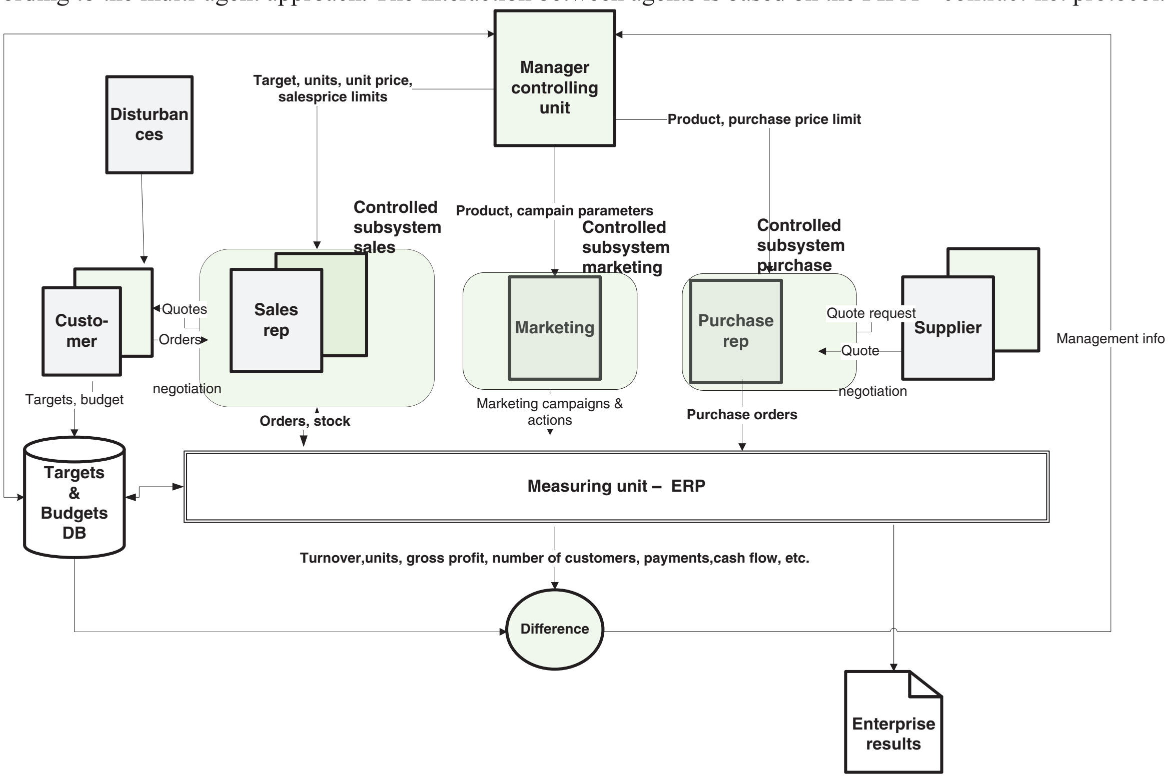

Fig. 1. Generic model of a business company. Source: adapted from Šperka et al.[4].

The number of customer agents is significantly higher than the number of seller agents in the model because the situation on the real market is the same. The behavior of agents is influenced by two randomly generated parameters: an amount of requested commodities using binomial distribution, and a sellers' ability to sell the commodities using normal distribution). In the lack of real information about the business company, there is a possibility to randomly generate more parameters (e.g. utility ratio of the current commodity, or an income of the customer). The influence of randomly generated parameters on the simulation outputs while using different types of distributions was previously described in Vymětal et al.[33].

4. Negotiation in details

In this section, the seller-to-customer negotiation workflow is described and the definition of the Marshallian demand function is proposed. Marshallian demand function is used during the contracting phase of agents' interaction. It serves to set up the limit price of the customer agent as an internal private parameter.

Only a part of the company's generic structure, defined earlier, was implemented. This part consists of the sellers and the customers trading with commodities (e.g. tables, chairs). One stock item simplification is used in the implementation. Participants of the contracting process in our multi-agent system are represented by the software agents - the seller and customer agents interacting in the course of the quotation, negotiation and contracting. There is an interaction between them. The behavior of the customer agent is characterized by the Marshallian demand function based on the Cobb-Douglas utility function.

In our previous experiments; e.g., Šperka and Spišák[34]; disturbance agent was used to correct the input data, based on the percentage calculation of the real data. Currently, after a change of a distribution for the quantity, disturbance agent is not used. Each period turn (here we assume a week), the customer agent decides whether to buy something. His decision is defined randomly. If the customer agent decides not to buy anything, his turn is over; otherwise he creates a sales request and sends it to his seller agent. Requested amount is generated using binomial distribution. The seller agent answers with a proposal message (a certain quote starting with his maximal price: *limit price * 1.25*). This quote can be accepted by the customer agent or not.

The customer agents evaluate the quotes according to the demand function by calculating his maximal price. The Marshallian demand function was derived from Cobb-Douglas utility function and represents the quantity of the traded commodity as the relationship between customer's income and the price of the demanded commodity. If the price quoted is lower than the customer's price obtained as a result of the demand function, the quote is accepted. In the opposite case, the customer rejects the quote and a negotiation is started. The seller agent decreases the price to the average of the minimal limit price and the current price (in every iteration is getting effectively closer and closer to the minimal limit price), and resends the quote back to the customer. The message exchange repeats until there is an agreement or a reserved time passes.

Marshallian function specifies what would consumer buy at each specific price and income, assuming it perfectly solves utility maximization problem. For example: If there are two commodities and the specific consumer's utility function is:

$$U(x_1, x_2) = x_1^{0,5} x_2^{0,5} U(x_1, x_2) = x_1^{0,5} x_2^{0,5} \tag{1}$$

Then the Marshallian demand function is a function of income and prices of commodities:

$$x(p_1, p_2, I) = \left(\frac{1}{2p_1}, \frac{1}{2p_2} \right) \tag{2}$$

Where I represents income and p_1 and p_2 are the prices of the commodities. In general, Cobb-Douglas utility function can be defined as:

$$U(x_1, x_2) = x_1^{\alpha} x_2^{1-\alpha} \tag{3}$$

The corresponding Marshallian demand function is:

$$x(p_1, p_2, I) = \left(\frac{\alpha I}{p_1}, \frac{(1-\alpha) I}{p_2} \right) \tag{4}$$

In the model there is calculated only one commodity (which is traded by the simulated company). In this case – using the Marshallian demand function there are two commodity baskets, where one is represented by company traded one and the rest represents all alternative commodities that customer can buy. So only x_1 is used supposing that utility ratio α is known and that for the rest of commodities the utility ratio is (1-α). Therefore the demand function looks like this:

$$x = S\frac{\alpha I}{p} \tag{5}$$

Where X represents amount of commodity, α is utility ratio, I is income and p is the price of the commodity. Customer's decision is described by retrieving the price from the demand function. We also include here the ability of the seller for increasing/decreasing the price according to his skills:

$$p = S\frac{\alpha I}{x} \tag{6}$$

This is the core formula, by which the customer decides if the quote is acceptable. The aforementioned parameters represent global simulation parameters set for each simulation experiment. Other global simulation parameters are:

- I – customer's income – it's normal distributed value generated at the beginning and not being changed during the generation;
- α – utility ratio – normal distributed value, which is generated for each customer each turn (week, while customers' preferences can change rapidly);
- p – commodity price;
- S – seller skills (ability to change price);
- x – amount of commodity – binomially distributed value generated, when customer decides to buy something.

Customer agents are organized in groups and each group is being served by specific seller agent. Their relationship is given; none of them can change the counterpart. Seller agent is responsible to the manager agent. Each turn, the manager agent gathers data from all seller agents and stores KPIs of the company. The data is the result of the simulation and serves to understand the company behavior in a time – depending on the agents' decisions and behavior. The customer agents need to know some information about the market. This information is given by the informative agent. This agent is also responsible for the turn management and represents outside or controllable phenomena from the agents' perspective.

5. Results and discussion

At the start of simulation experiments phase some parameters were set. Agent count and their parameterization are listed in Table 1. The purpose of the simulations is to prove if the demand functions could serve as a core element in the seller-to-customer negotiation.

Table 1. Multi-agent system parameterization.

Agent Type	Agent Count	Parameter Name	Parameter Value
Customer Agent	500	Maximum Discussion Turns	10
		Max Quantity	800 m
		Probability to get Max Quantity	0.1667
		Mean Income	600 EUR
		Income Standard Dev.	10
		Mean Utility Ratio	1.15
		Utility Standard Dev.	0.2
Seller Agent	25	Mean Ability	1
		Ability Standard Deviation	0.03
		Minimal Price	0.36 EUR
Manager Agent	1	Purchase Price	0.17 EUR
Market Info	1	Iterations count	52 weeks

Agents were simulating one year – 52 weeks of interactions. As mentioned above – manager agent was calculating the KPIs. The results of the simulation are shown in graph (Fig. 2). The results are depicted in four categories frequently used to describe the company's trading balance. The categories are: sold amount, income, costs, and gross profit.

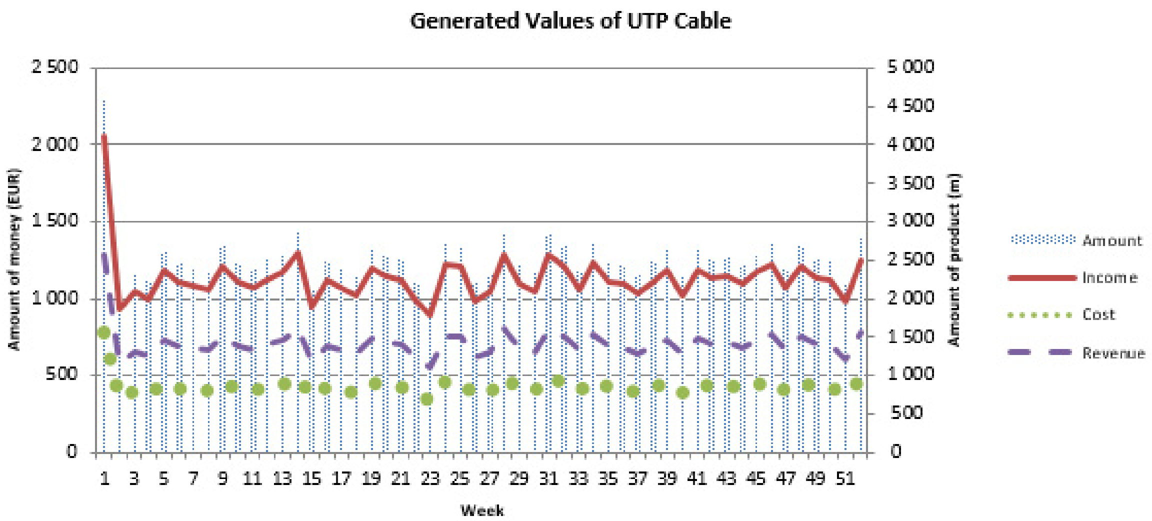

Fig. 2. KPIs results for 1 year generation.

The commodity to be traded with was a UTP cable. Of course, companies are dealing with a whole portfolio of products. In our simplification we concentrated only on one product and this was a UTP cable. Further, average gross profit was chosen as a representative KPI. Figure 3 contains the month averages of total gross profit for real and generated data. As can be seen from this figure, the result of simulation represents trend, which is quite similar to the real data.

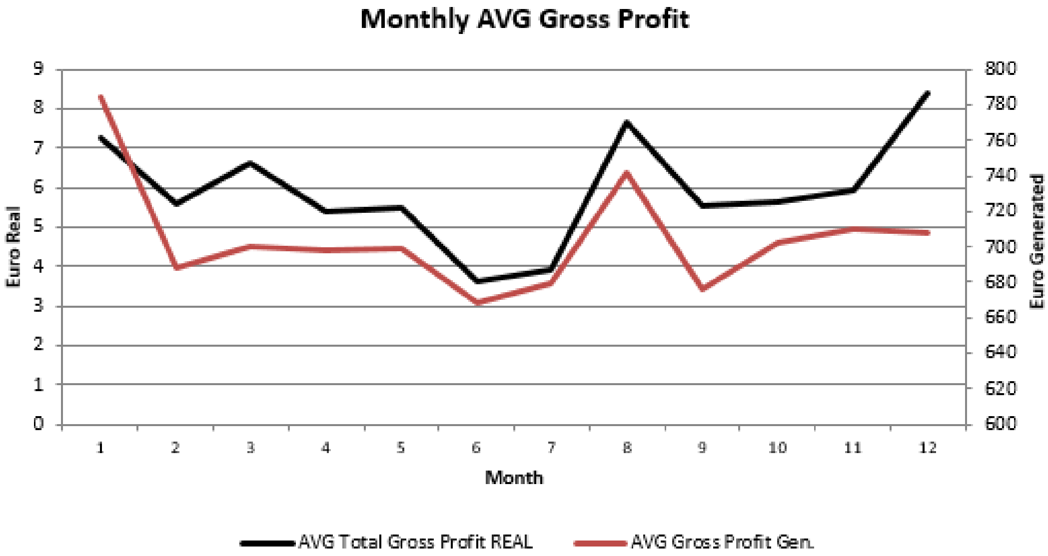

Fig. 3. The generation values graph – monthly.

Real data was taken from a Slovak anonymous company trading with PC components and supplies. The time series was discovered for the 2012 and the parameters of the simulations were set to mirror the situation on the market in that time.

To see the correlation between the real and generated total month profit the correlation analysis was done. Correlation coefficient for the average gross profit amount was 0.69, which represents quite strong correlation between real and generated data. These results show that the demand functions could be used in further experiments to support the predictive purposes of decision making tools based on it.

6. Conclusion

The paper introduces an experimental business management approach to cover a seller-to-customer price negotiation in an agent-based simulations. The core element in this approach is the price negotiation. We used Marshallian demand function and a Cobb-Douglas utility function in the negotiation process within a virtual business company. The experiments were set to prove the idea, that microeconomic demand functions could be used as a core element in seller-to-customer price negotiation. The overall idea is to use this approach to implement decision support models that could be connected to real management information systems in order to serve as a prediction modules. We obtained successful results in some of the KPIs of a company (gross profit averages measured monthly). This supports our motivation to proceed with the experiments, to enhance our approach to extend the results on the rest of the KPIs.

In our future research we will concentrate on the enhancement of the approach proposed. We will make a comparison of the simulation results with other microeconomic models such as a decision functions, and we will focus on the implementation of a Monte Carlo simulation to compare agent-based model with classical approach.

Acknowledgements

This work was supported by the grant: Innovation of Study Programs at Silesian University in Opava, School of Business Administration in Karvina, Reg. no. CZ.1.07/2.2.00/28.0017.

References

1. Bucki R, Suchánek P. The Method of Logistic Optimization in E-commerce. *Journal of universal computer science*, Volume **18**, Issue 10, Austria; 2012, pp. 1238-1258.
2. Šperka R. Application of a Simulation Framework for Decision Support Systems. *Mitteilungen Klosterneuburg*, Hoehere Bundeslehranstalt und Bundesamt fuer Wein- und Obstbau, Klosterneuburg, Austria, 2014. Volume **64**, Issue 1, ISSN 0007-5922, 2014.
3. Šperka R, Vymětal D, Spišák M. Towards the Validation of Agent-based BPM Simulation. In: *Proc. Advanced Methods and Technologies for Agent and Multi-agent Systems. Frontiers in Artificial Intelligence and Applications.* 7th International Conference KES-AMSTA`13, Hue city, Vietnam, 27.-29.5.2013. Amsterdam: IOS Press BV, Netherlands, Volume 252, pp. 276-283. ISBN 978-1-61499-253-0 (print), ISBN 978-61499-254-7 (online), 2013.
4. Šperka R, Spišák M, Slaninová K, Martinovič J, Dráždilová P. Control Loop Model of Virtual Company in BPM Simulation. In: *Proc. Advances in Intelligent Systems and Computing. Soft Computing Models in Industrial and Environmental Applications*. Berlin Heidelberg: Springer-Verlag, Germany, Volume 188, pp. 515-524. DOI: 10.1007/978-3-642-32922-7_53. ISSN 2194-5357. ISBN 978-3-642-32921-0, 2013.
5. Šperka R, Spišák M. Transaction Costs Influence on the Stability of Financial Market: Agent-based Simulation. *Journal of Business Economics and Management*, Taylor & Francis, London, United Kingdom, 2013. Volume **14**, Supplement 1, DOI: 10.3846/16111699.2012.701227. Print ISSN 1611-1699, Online ISSN 2029-4433. Available from: <http://www.tandfonline.com/doi/abs/10.3846/16111699.2012.701227#.Ur80j9LuLy0>. (Accessed 31 January 2014), pp. S1-S12, 2014.
6. Šperka R, Vymětal D. MAREA - an Education Application for Trading Company Simulation based on REA Principles. In: *Proc. Advances in Education Research*. Vol. 30. Information, Communication and Education Application. USA. pp. 140-147. ISBN 978-1-61275-056-9, 2013.
7. Barnett M. Modeling & Simulation in Business Process Management', Gensym Corporation, [online], Available from: < http://news.bptrends .com/publicationfiles/1103%20WP%20Mod%20Simulation%20of%20BPM%20-%20Barnett-1.pdf> (Accessed 16 January 2012); 2003, pp. 6-7.
8. Enis BM. *Marketing principles: the management process*. Goodyear Pub. Co., Pacific Palisades, California, 608 p., ISBN 0876205503, 1974.
9. McCarthy EJ, Perreault WD. *Basic marketing: a global-managerial approach*. Irwin, 792 p., ISBN 025610509X, 1993.
10. Keegan W, Moriarty S, Duncan T. *Marketing*. Prentice-Hall. Englewood Cliffs. New Jersey. 1992, 193 p.
11. Schiffman LG, Kanuk LL. *Purchasing Behavior*. 9th ed. Upper Saddle River, NJ: Pearson Prentice Hall, 2007.
12. Gregson N, Crewe L, Brooks K. Shopping, space, and practice. In: *Environment and Planning* D **20** (5), pp. 597–617. DOI: 10.1068/d270t, 2002.
13. Jackson P, Perez Del Aguila RP, Clarke I, Hallsworth A, De Kervenoael R, Kirkup, M. Retail restructuring and consumer choice 2. Understanding consumer choice at the household level. In*: Environment and Planning*. Vol. **A38**, isuue 1, pp. 47–67. DOI: 10.1068/a37208, 2006.
14. Forrester J. Planung unter dem Einfluss komplexer Sozialer Systeme. In: *Politische Planung in Theorie und Praxis*. Ed by. G. Schmieg. Piper Verlag. München; 1971, 88 p.
15. Challet D, Krause A. What questions to ask in order to validate an agent-based model. In: *Report of the 56th European Study Group with Industry*, pp. J1-J9 [online]. Available from: < http://www .maths-in-industry.org/ mi-is/107/1/Unilever-ABM-Report.pdf> (Accessed 28 March 2013), 2006.
16. Tay N, Lusch R. Agent-Based Modeling of Ambidextrous Organizations: Virtualizing Competitive Strategy. IEEE *Transactions on Intelligent Systems*, Vol. **22**, issue 5; 2002, pp. 50-57.
17. Wilkinson I, Young L. On cooperating: Firms. Relations. Networks. *Journal of Business Research*. Issue 55; 2002, pp. 123-132.
18. Casti J. *Would-be Worlds. How Simulation is Changing the World of Science*. Wiley. New York, 1997.
19. Goldenberg J, Libai B, Muller E. The Chilling effect of network externalities. *International Journal of Research in Marketing*. **27**(1); 2010, pp. 4-15.
20. Heath B, Hill R, Ciarallo F. A survey of agent-based modeling practices (January 1998 to July 2008). *Journal of Artificial Societies and Social Simulation*. Vol. **12**, issue 4; 2009, pp. 5-32.
21. Rahmandad H, Sterman J. Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. *Management Science*. Vol. **54**, issue 5; 2008, pp. 998-1014.
22. Shaikh N, Ragaswamy A, Balakrishnan A. *Modelling the Diffusion of Innovations Using Small World Networks*. Working Paper. Penn State University. Philadelphia, 2005.
23. Toubia O, Goldenberg J, Garcia R. *A New approach to modeling the adoption of new products: Aggregated Diffusion Models*. MSI Reports: Working Papers Series. Vol. 8, issue 1; 2008, pp. 65-76.
24. Laco P. Innovations in Corporate Internet Usage. Acta Periodica. No.6 (1/2010), Tatabánya: *Scientific journal of College for Modern Business Studies in Tatabanya*, ISSN 1786-6421; 2010, pp. 113-122.
25. Adjali I, Dias B, Hurling R. Agent based modeling of consumer behavior. In: *Proceedings of the North American Association for Computational Social and Organizational Science Annual Conference*. University of Notre Dame. Notre Dame (2005). Indiana, [online]. Available from: <http://www.casos.cs.cmu.edu/events/ conferences/2005/conference> (Accessed 14 March 2012), 2005.
26. Ben L, Bouron T, Drogoul A. Agent-based interaction analysis of consumer behavior. In: *Proceedings of the first international joint conference on Autonomous agents and multiagent systems: part 1*. ACM. New York; 2002, pp. 184-190.

27. Collings D, Reeder A, Adjali I, Crocker P, Lyons M. Agent based customer modelling. *Computing in Economics and Finance*. (1999), No. **1352** [online]. Available from: <http://econpapers.repec.org/paper /scescecf9/1352.htm> (Accessed 28 March 2013), 1999.
28. Marshall A. *Principle of Economics*. 8th Ed. MacMillan, London, 1920.
29. Mas-Colell A, Whinston M, Green J. *Microeconomic Theory*. Oxford: Oxford University Press. ISBN 0-19-507340-1, 1995.
30. Pollak R. Conditional Demand Functions and Consumption Theory. *Quarterly Journal of Economics*, **83**; 1969, pp. 60-78.
31. Varian HR. *Microeconomic Analysis*. Third Edition. W.W. Norton & Company, New York, Chapters 7, 8 and 9, 1992.
32. Foundation for Intelligent Physical Agents (FIPA). *FIPA Contract Net Interaction Protocol*. In Specification [online]. FIPA, Available from: <http://www.fipa.org/specs/fipa00029/SC00029H.pdf>. (Accessed 13 June 2013), 2002.
33. Vymětal D, Spišák M, Šperka R. An Influence of Random Number Generation Function to Multiagent Systems. In: *Proc. LNAI 7327. Agent and Multi-Agent Systems. Technologies and Applications*. 6th KES International Conference, KES-AMSTA 2012, Dubrovnik, Croatia. Berlin Heidelberg: Springer-Verlag, Germany, pp.340-349. ISSN 0302-9743. ISBN 978-3-642-30946-5. DOI 10.1007/978-3-642-30946-5. Available from: http://www.springerlink.com/content/g71k68505h76x1wx/, 2012.
34. Šperka R, Spišák M. Microeconomic Demand Functions Implementation in Java Experiments. In: *Proc. Advances in Intelligent Systems and Computing*, Volume 296, 2014, Agent and Multi-Agent Systems. Technologies and Applications. 8th KES International Conference, KES AMSTA 2014, Chania, Greece. Berlin Heidelberg: Springer International Publishing, Germany, pp.183-192. Series ISSN 2194-5357. ISBN 978-3-319-07649-2. DOI 10.1007/978-3-319-07650-8_19.Available from: <http://link.springer.com/chapter/10.1007/978-3-319-07650-8_19>.